autogluon_each_location

October 16, 2023

[1]:
```
# config

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60*5
presets = 'best_quality'

do_drop_ds = True
# hour, dayofweek, dayofmonth, month, year
use_dt_attrs = []#["hour", "year"]
use_estimated_diff_attr = False
use_is_estimated_attr = True

use_groups = False
n_groups = 8

auto_stack = True
num_stack_levels = 1
num_bag_folds = 0
if auto_stack:
    num_stack_levels = None
    num_bag_folds = None

use_tune_data = False
use_test_data = True
tune_and_test_length = 24*30*3 # 3 months from end
holdout_frac = None
use_bag_holdout = False # Enable this if there is a large gap between score_val␣
 ↪and score_test in stack models.

sample_weight = None#'sample_weight' #None
weight_evaluation = False
sample_weight_estimated = 1

run_analysis = True
```

[2]:
```python
import pandas as pd
import numpy as np



import warnings
warnings.filterwarnings("ignore")


def feature_engineering(X):
    # shift all columns with "1h" in them by 1 hour, so that for index 16:00,␣
 ↪we have the values from 17:00
    # but only for the columns with "1h" in the name
    #X_shifted = X.filter(regex="\dh").shift(-1, axis=1)
    #print(f"Number of columns with 1h in name: {X_shifted.columns}")


    columns = ['clear_sky_energy_1h:J', 'diffuse_rad_1h:J', 'direct_rad_1h:J',
       'fresh_snow_12h:cm', 'fresh_snow_1h:cm', 'fresh_snow_24h:cm',
       'fresh_snow_3h:cm', 'fresh_snow_6h:cm']

    X_shifted = X[X.index.minute==0][columns].shift(-1, axis=0)
    X_old_unshifted = X[X.index.minute==0][columns]
    # rename X_old_unshifted columns to have _not_shifted at the end
    X_old_unshifted.columns = [f"{col}_not_shifted" for col in X_old_unshifted.
 ↪columns]

    # put the shifted columns back into the original dataframe
    #X[columns] = X_shifted[columns]




    date_calc = None
    if "date_calc" in X.columns:
        date_calc = X[X.index.minute == 0]['date_calc']

    # resample to hourly
    X = X.resample('H').mean()

    X[columns] = X_shifted[columns]
    X[X_old_unshifted.columns] = X_old_unshifted

    if date_calc is not None:
        X['date_calc'] = date_calc

    return X
```

```python
def fix_X(X, name):
    # Convert 'date_forecast' to datetime format and replace original column with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)


    X = feature_engineering(X)

    return X



def handle_features(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_X(X_train_observed, "X_train_observed")
    X_train_estimated = fix_X(X_train_estimated, "X_train_estimated")
    X_test = fix_X(X_test, "X_test")


    # add sample weights, which are 1 for observed and 3 for estimated
    X_train_observed["sample_weight"] = 1
    X_train_estimated["sample_weight"] = sample_weight_estimated
    X_test["sample_weight"] = sample_weight_estimated


    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train, location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train = handle_features(X_train_observed, X_train_estimated, X_test, y_train)

    if use_estimated_diff_attr:
```

```python
        X_train_observed["estimated_diff_hours"] = 0
        X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index -␣
↪pd.to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
        X_test["estimated_diff_hours"] = (X_test.index - pd.
↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600

        X_train_estimated["estimated_diff_hours"] =␣
↪X_train_estimated["estimated_diff_hours"].astype('int64')
        # the filled once will get dropped later anyways, when we drop y nans
        X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].
↪fillna(-50).astype('int64')

    if use_is_estimated_attr:
        X_train_observed["is_estimated"] = 0
        X_train_estimated["is_estimated"] = 1
        X_test["is_estimated"] = 1

    # drop date_calc
    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)


    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="inner", left_index=True,␣
↪right_index=True)

    # print number of nans in sample_weight
    print(f"Number of nans in sample_weight: {X_train['sample_weight'].isna().
↪sum()}")
    # print number of nans in y
    print(f"Number of nans in y: {X_train['y'].isna().sum()}")


    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']
```

```
X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
 ↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
Number of nans in sample_weight: 0
Number of nans in y: 0
Processing location B…
Number of nans in sample_weight: 0
Number of nans in y: 4
Processing location C…
Number of nans in sample_weight: 0
Number of nans in y: 6059
```

1 Feature enginering

[3]:
```
import numpy as np
import pandas as pd

X_train.dropna(subset=['y'], inplace=True)
```

```
for attr in use_dt_attrs:
    X_train[attr] = getattr(X_train.index, attr)
    X_test[attr] = getattr(X_test.index, attr)

print(X_train.head())
```

```
if use_groups:
    # fix groups for cross validation
    locations = X_train['location'].unique()  # Assuming 'location' is the name␣
 ↪of the column representing locations

    grouped_dfs = []  # To store data frames split by location

    # Loop through each unique location
    for loc in locations:
        loc_df = X_train[X_train['location'] == loc]

        # Sort the DataFrame for this location by the time column
        loc_df = loc_df.sort_index()

        # Calculate the size of each group for this location
        group_size = len(loc_df) // n_groups

        # Create a new 'group' column for this location
        loc_df['group'] = np.repeat(range(n_groups),␣
 ↪repeats=[group_size]*(n_groups-1) + [len(loc_df) - group_size*(n_groups-1)])

        # Append to list of grouped DataFrames
        grouped_dfs.append(loc_df)

    # Concatenate all the grouped DataFrames back together
    X_train = pd.concat(grouped_dfs)
    X_train.sort_index(inplace=True)
    print(X_train["group"].head())
```

```
to_drop = ["snow_drift:idx", "snow_density:kgm3"]

X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)
```

```python
X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

```
                     absolute_humidity_2m:gm3  air_density_2m:kgm3  \
ds
2019-06-02 22:00:00                     7.700              1.22825
2019-06-02 23:00:00                     7.700              1.22350
2019-06-03 00:00:00                     7.875              1.21975
2019-06-03 01:00:00                     8.425              1.21800
2019-06-03 02:00:00                     8.950              1.21800

                     ceiling_height_agl:m  clear_sky_energy_1h:J  \
ds
2019-06-02 22:00:00           1728.949951               0.000000
2019-06-02 23:00:00           1689.824951               0.000000
2019-06-03 00:00:00           1563.224976               0.000000
2019-06-03 01:00:00           1283.425049            6546.899902
2019-06-03 02:00:00           1003.500000          102225.898438

                     clear_sky_rad:W  cloud_base_agl:m  dew_or_rime:idx  \
ds
2019-06-02 22:00:00             0.00       1728.949951              0.0
2019-06-02 23:00:00             0.00       1689.824951              0.0
2019-06-03 00:00:00             0.00       1563.224976              0.0
2019-06-03 01:00:00             0.75       1283.425049              0.0
2019-06-03 02:00:00            23.10       1003.500000              0.0

                     dew_point_2m:K  diffuse_rad:W  diffuse_rad_1h:J  …  \
ds                                                                    …
2019-06-02 22:00:00      280.299988          0.000          0.000000  …
2019-06-02 23:00:00      280.299988          0.000          0.000000  …
2019-06-03 00:00:00      280.649994          0.000          0.000000  …
2019-06-03 01:00:00      281.674988          0.300       7743.299805  …
2019-06-03 02:00:00      282.500000         11.975      60137.601562  …

                     direct_rad_1h:J_not_shifted  \
ds
2019-06-02 22:00:00                          0.0
2019-06-02 23:00:00                          0.0
2019-06-03 00:00:00                          0.0
2019-06-03 01:00:00                          0.0
2019-06-03 02:00:00                          0.0

                     fresh_snow_12h:cm_not_shifted  \
ds
2019-06-02 22:00:00                            0.0
2019-06-02 23:00:00                            0.0
2019-06-03 00:00:00                            0.0
```

```
2019-06-03 01:00:00                            0.0
2019-06-03 02:00:00                            0.0

                    fresh_snow_1h:cm_not_shifted  \
ds
2019-06-02 22:00:00                          0.0
2019-06-02 23:00:00                          0.0
2019-06-03 00:00:00                          0.0
2019-06-03 01:00:00                          0.0
2019-06-03 02:00:00                          0.0

                    fresh_snow_24h:cm_not_shifted  \
ds
2019-06-02 22:00:00                            0.0
2019-06-02 23:00:00                            0.0
2019-06-03 00:00:00                            0.0
2019-06-03 01:00:00                            0.0
2019-06-03 02:00:00                            0.0

                    fresh_snow_3h:cm_not_shifted  \
ds
2019-06-02 22:00:00                          0.0
2019-06-02 23:00:00                          0.0
2019-06-03 00:00:00                          0.0
2019-06-03 01:00:00                          0.0
2019-06-03 02:00:00                          0.0

                    fresh_snow_6h:cm_not_shifted  sample_weight  \
ds
2019-06-02 22:00:00                          0.0              1
2019-06-02 23:00:00                          0.0              1
2019-06-03 00:00:00                          0.0              1
2019-06-03 01:00:00                          0.0              1
2019-06-03 02:00:00                          0.0              1

                    is_estimated      y  location
ds
2019-06-02 22:00:00             0   0.00         A
2019-06-02 23:00:00             0   0.00         A
2019-06-03 00:00:00             0   0.00         A
2019-06-03 01:00:00             0   0.00         A
2019-06-03 02:00:00             0  19.36         A

[5 rows x 57 columns]
```

[4]:
```python
from autogluon.tabular import TabularDataset, TabularPredictor
from autogluon.timeseries import TimeSeriesDataFrame
```

```python
import numpy as np
train_data = TabularDataset('X_train_raw.csv')
# set group column of train_data be increasing from 0 to 7 based on time, the␣
↪first 1/8 of the data is group 0, the second 1/8 of the data is group 1, etc.
train_data['ds'] = pd.to_datetime(train_data['ds'])
train_data = train_data.sort_values(by='ds')

# # print size of the group for each location
# for loc in locations:
#     print(f"Location {loc}:")
#     print(train_data[train_data["location"] == loc].groupby('group').size())


# get end date of train data and subtract 3 months
split_time = pd.to_datetime(train_data["ds"]).max() - pd.
↪Timedelta(hours=tune_and_test_length)
train_set = TabularDataset(train_data[train_data["ds"] < split_time])
test_set = TabularDataset(train_data[train_data["ds"] >= split_time])
if use_groups:
    test_set = test_set.drop(columns=['group'])

if do_drop_ds:
    train_set = train_set.drop(columns=['ds'])
    test_set = test_set.drop(columns=['ds'])
    train_data = train_data.drop(columns=['ds'])


def normalize_sample_weights_per_location(df):
    for loc in locations:
        loc_df = df[df["location"] == loc]
        loc_df["sample_weight"] = loc_df["sample_weight"] /␣
↪loc_df["sample_weight"].sum() * loc_df.shape[0]
        df[df["location"] == loc] = loc_df
    return df

tuning_data = None
if use_tune_data:
    train_data = train_set
    if use_test_data:
        # split test_set in half, use first half for tuning
        tuning_data, test_data = [], []
        for loc in locations:
            loc_test_set = test_set[test_set["location"] == loc]
            loc_tuning_data = loc_test_set.iloc[:len(loc_test_set)//2]
            loc_test_data = loc_test_set.iloc[len(loc_test_set)//2:]
            tuning_data.append(loc_tuning_data)
            test_data.append(loc_test_data)
```

```
        tuning_data = pd.concat(tuning_data)
        test_data = pd.concat(test_data)
        print("Shapes of tuning and test", tuning_data.shape[0], test_data.
↪shape[0], tuning_data.shape[0] + test_data.shape[0])

    else:
        tuning_data = test_set
        print("Shape of tuning", tuning_data.shape[0])

    # ensure sample weights for your tuning data sum to the number of rows in␣
↪the tuning data.
    tuning_data = normalize_sample_weights_per_location(tuning_data)


else:
    if use_test_data:
        train_data = train_set
        test_data = test_set
        print("Shape of test", test_data.shape[0])

# ensure sample weights for your training (or tuning) data sum to the number of␣
↪rows in the training (or tuning) data.
train_data = normalize_sample_weights_per_location(train_data)
if use_test_data:
    test_data = normalize_sample_weights_per_location(test_data)
```

```
Shape of test 5791
```

[5]:
```
if run_analysis:
    import autogluon.eda.auto as auto
    auto.dataset_overview(train_data=train_data, test_data=test_data,␣
↪label="y", sample=None)
```

train_data dataset summary

	count	unique	top	freq	mean	\
absolute_humidity_2m:gm3	87160	757			6.138632	
air_density_2m:kgm3	87160	1370			1.253802	
ceiling_height_agl:m	72139	59833			2864.542561	
clear_sky_energy_1h:J	87160	45557			518223.98768	
clear_sky_energy_1h:J_not_shifted	87160	45557			518234.059562	
clear_sky_rad:W	87160	19511			143.951884	
cloud_base_agl:m	81279	61233			1736.160546	
dew_or_rime:idx	87160	9			0.009491	
dew_point_2m:K	87160	2001			275.537267	
diffuse_rad:W	87160	10980			39.210491	
diffuse_rad_1h:J	87160	45515			141509.744358	
diffuse_rad_1h:J_not_shifted	87160	45515			141510.381097	

```
direct_rad:W                      87160   13914                 50.139922
direct_rad_1h:J                   87160   39280             180354.638612
direct_rad_1h:J_not_shifted       87160   39281             180365.163277
effective_cloud_cover:p           87160    5652                 67.118857
elevation:m                       87160       3                 11.411014
fresh_snow_12h:cm                 87160     121                  0.096432
fresh_snow_12h:cm_not_shifted     87160     121                  0.096392
fresh_snow_1h:cm                  87160      39                  0.008136
fresh_snow_1h:cm_not_shifted      87160      39                  0.008132
fresh_snow_24h:cm                 87160     158                  0.191661
fresh_snow_24h:cm_not_shifted     87160     158                  0.191621
fresh_snow_3h:cm                  87160      68                  0.024312
fresh_snow_3h:cm_not_shifted      87160      68                  0.024302
fresh_snow_6h:cm                  87160      94                  0.048428
fresh_snow_6h:cm_not_shifted      87160      94                  0.048398
is_day:idx                        87160       5                  0.482965
is_estimated                      87232       2                   0.05968
is_in_shadow:idx                  87160       5                  0.564895
location                          87232       3   A  31924
msl_pressure:hPa                  87160    3693               1009.291473
precip_5min:mm                    87160     270                  0.005788
precip_type_5min:idx              87160      15                  0.084236
pressure_100m:hPa                 87160    3705                995.621975
pressure_50m:hPa                  87160    3758               1001.745166
prob_rime:p                       87160    1723                  0.697669
rain_water:kgm2                   87160      39                  0.010136
relative_humidity_1000hPa:p       87160    3787                 73.860635
sample_weight                     87232       1                       1.0
sfc_pressure:hPa                  87160    3780                1007.89561
snow_depth:cm                     87160     483                  0.197251
snow_melt_10min:mm                87160      63                  0.000245
snow_water:kgm2                   87160     161                   0.09109
sun_azimuth:d                     87160   82801                179.660078
sun_elevation:d                   87160   71854                 -1.225457
super_cooled_liquid_water:kgm2    87160      53                  0.058341
t_1000hPa:K                       87160    1986                279.712685
total_cloud_cover:p               87160    5546                 73.819247
visibility:m                      87160   85645              33233.674454
wind_speed_10m:ms                 87160     594                  3.025581
wind_speed_u_10m:ms               87160     988                  0.664335
wind_speed_v_10m:ms               87160     848                  0.694845
wind_speed_w_1000hPa:ms           87160       9                  0.000002
y                                 87232   10750                287.954185

                                        std      min         25%  \
absolute_humidity_2m:gm3            2.73761      0.5         4.1
air_density_2m:kgm3                0.036657  1.13925     1.22875
ceiling_height_agl:m            2531.428872     27.8   1085.2625
```

clear_sky_energy_1h:J	828407.396747	0.0	0.0
clear_sky_energy_1h:J_not_shifted	828409.158425	0.0	0.0
clear_sky_rad:W	230.149085	0.0	0.0
cloud_base_agl:m	1797.954658	27.8	598.2875
dew_or_rime:idx	0.234376	-1.0	0.0
dew_point_2m:K	6.846723	247.425	271.0
diffuse_rad:W	60.603659	0.0	0.0
diffuse_rad_1h:J	216223.834057	0.0	0.0
diffuse_rad_1h:J_not_shifted	216223.195823	0.0	0.0
direct_rad:W	113.07899	0.0	0.0
direct_rad_1h:J	402272.467762	0.0	0.0
direct_rad_1h:J_not_shifted	402279.826859	0.0	0.0
effective_cloud_cover:p	34.037938	0.0	42.41875
elevation:m	7.881548	6.0	6.0
fresh_snow_12h:cm	0.735619	0.0	0.0
fresh_snow_12h:cm_not_shifted	0.735566	0.0	0.0
fresh_snow_1h:cm	0.107502	0.0	0.0
fresh_snow_1h:cm_not_shifted	0.107497	0.0	0.0
fresh_snow_24h:cm	1.140022	0.0	0.0
fresh_snow_24h:cm_not_shifted	1.139991	0.0	0.0
fresh_snow_3h:cm	0.267721	0.0	0.0
fresh_snow_3h:cm_not_shifted	0.26771	0.0	0.0
fresh_snow_6h:cm	0.45772	0.0	0.0
fresh_snow_6h:cm_not_shifted	0.457678	0.0	0.0
is_day:idx	0.485944	0.0	0.0
is_estimated	0.236894	0.0	0.0
is_in_shadow:idx	0.483131	0.0	0.0
location			
msl_pressure:hPa	12.998509	944.375	1001.275
precip_5min:mm	0.029771	0.0	0.0
precip_type_5min:idx	0.325388	0.0	0.0
pressure_100m:hPa	12.924683	929.975	987.69995
pressure_50m:hPa	12.982562	935.75	993.75
prob_rime:p	5.08106	0.0	0.0
rain_water:kgm2	0.042332	0.0	0.0
relative_humidity_1000hPa:p	14.160229	19.575	64.425
sample_weight	0.0	1.0	1.0
sfc_pressure:hPa	13.042592	941.55	999.85
snow_depth:cm	1.284395	0.0	0.0
snow_melt_10min:mm	0.003958	0.0	0.0
snow_water:kgm2	0.240712	0.0	0.0
sun_azimuth:d	97.308971	6.983	94.72475
sun_elevation:d	24.168008	-49.932	-18.737563
super_cooled_liquid_water:kgm2	0.106882	0.0	0.0
t_1000hPa:K	6.559438	258.025	275.15
total_cloud_cover:p	33.768818	0.0	53.725
visibility:m	18089.724083	132.375	16688.61875
wind_speed_10m:ms	1.752114	0.025	1.65

wind_speed_u_10m:ms	2.779236	-7.225	-1.35
wind_speed_v_10m:ms	1.881059	-8.4	-0.55
wind_speed_w_1000hPa:ms	0.006041	-0.1	0.0
y	766.111697	0.0	0.0

	50%	75%	max	dtypes \
absolute_humidity_2m:gm3	5.6	8.0	17.35	float64
air_density_2m:kgm3	1.2525	1.27675	1.441	float64
ceiling_height_agl:m	1859.4751	3925.32485	12285.775	float64
clear_sky_energy_1h:J	4304.55	777057.95	3006697.2	float64
clear_sky_energy_1h:J_not_shifted	4309.0	777229.375	3006697.2	float64
clear_sky_rad:W	1.6	216.2	835.65	float64
cloud_base_agl:m	1178.425	2081.0375	11673.725	float64
dew_or_rime:idx	0.0	0.0	1.0	float64
dew_point_2m:K	275.4	280.8	293.625	float64
diffuse_rad:W	0.875	64.325	334.75	float64
diffuse_rad_1h:J	9533.25	232995.65	1182265.4	float64
diffuse_rad_1h:J_not_shifted	9534.75	232989.0	1182265.4	float64
direct_rad:W	0.0	28.925	683.4	float64
direct_rad_1h:J	0.0	111380.225	2445897.0	float64
direct_rad_1h:J_not_shifted	0.0	111410.2	2445897.0	float64
effective_cloud_cover:p	79.675	98.475	100.0	float64
elevation:m	7.0	24.0	24.0	float64
fresh_snow_12h:cm	0.0	0.0	37.4	float64
fresh_snow_12h:cm_not_shifted	0.0	0.0	37.4	float64
fresh_snow_1h:cm	0.0	0.0	7.1	float64
fresh_snow_1h:cm_not_shifted	0.0	0.0	7.1	float64
fresh_snow_24h:cm	0.0	0.0	37.4	float64
fresh_snow_24h:cm_not_shifted	0.0	0.0	37.4	float64
fresh_snow_3h:cm	0.0	0.0	20.6	float64
fresh_snow_3h:cm_not_shifted	0.0	0.0	20.6	float64
fresh_snow_6h:cm	0.0	0.0	34.0	float64
fresh_snow_6h:cm_not_shifted	0.0	0.0	34.0	float64
is_day:idx	0.25	1.0	1.0	float64
is_estimated	0.0	0.0	1.0	int64
is_in_shadow:idx	1.0	1.0	1.0	float64
location				object
msl_pressure:hPa	1010.275	1018.35	1044.1	float64
precip_5min:mm	0.0	0.0	0.6225	float64
precip_type_5min:idx	0.0	0.0	5.0	float64
pressure_100m:hPa	996.7	1004.7	1030.875	float64
pressure_50m:hPa	1002.8	1010.825	1037.25	float64
prob_rime:p	0.0	0.0	96.775	float64
rain_water:kgm2	0.0	0.0	1.1	float64
relative_humidity_1000hPa:p	76.2	85.25	100.0	float64
sample_weight	1.0	1.0	1.0	int64
sfc_pressure:hPa	1008.925	1017.0	1043.725	float64
snow_depth:cm	0.0	0.0	18.2	float64

snow_melt_10min:mm	0.0	0.0	0.18	float64
snow_water:kgm2	0.0	0.1	5.65	float64
sun_azimuth:d	180.007	264.513	348.48752	float64
sun_elevation:d	-0.8645	15.234063	49.94375	float64
super_cooled_liquid_water:kgm2	0.0	0.1	1.375	float64
t_1000hPa:K	279.075	284.25	303.25	float64
total_cloud_cover:p	92.85	99.9	100.0	float64
visibility:m	37320.0515	48663.7615	75489.33	float64
wind_speed_10m:ms	2.7	4.05	13.275	float64
wind_speed_u_10m:ms	0.3	2.475	11.2	float64
wind_speed_v_10m:ms	0.725	1.875	8.825	float64
wind_speed_w_1000hPa:ms	0.0	0.0	0.1	float64
y	0.0	176.4	5733.42	float64

	missing_count	missing_ratio	raw_type	\
absolute_humidity_2m:gm3	72	0.000825	float	
air_density_2m:kgm3	72	0.000825	float	
ceiling_height_agl:m	15093	0.173021	float	
clear_sky_energy_1h:J	72	0.000825	float	
clear_sky_energy_1h:J_not_shifted	72	0.000825	float	
clear_sky_rad:W	72	0.000825	float	
cloud_base_agl:m	5953	0.068243	float	
dew_or_rime:idx	72	0.000825	float	
dew_point_2m:K	72	0.000825	float	
diffuse_rad:W	72	0.000825	float	
diffuse_rad_1h:J	72	0.000825	float	
diffuse_rad_1h:J_not_shifted	72	0.000825	float	
direct_rad:W	72	0.000825	float	
direct_rad_1h:J	72	0.000825	float	
direct_rad_1h:J_not_shifted	72	0.000825	float	
effective_cloud_cover:p	72	0.000825	float	
elevation:m	72	0.000825	float	
fresh_snow_12h:cm	72	0.000825	float	
fresh_snow_12h:cm_not_shifted	72	0.000825	float	
fresh_snow_1h:cm	72	0.000825	float	
fresh_snow_1h:cm_not_shifted	72	0.000825	float	
fresh_snow_24h:cm	72	0.000825	float	
fresh_snow_24h:cm_not_shifted	72	0.000825	float	
fresh_snow_3h:cm	72	0.000825	float	
fresh_snow_3h:cm_not_shifted	72	0.000825	float	
fresh_snow_6h:cm	72	0.000825	float	
fresh_snow_6h:cm_not_shifted	72	0.000825	float	
is_day:idx	72	0.000825	float	
is_estimated			int	
is_in_shadow:idx	72	0.000825	float	
location			object	
msl_pressure:hPa	72	0.000825	float	
precip_5min:mm	72	0.000825	float	

precip_type_5min:idx	72	0.000825	float
pressure_100m:hPa	72	0.000825	float
pressure_50m:hPa	72	0.000825	float
prob_rime:p	72	0.000825	float
rain_water:kgm2	72	0.000825	float
relative_humidity_1000hPa:p	72	0.000825	float
sample_weight			int
sfc_pressure:hPa	72	0.000825	float
snow_depth:cm	72	0.000825	float
snow_melt_10min:mm	72	0.000825	float
snow_water:kgm2	72	0.000825	float
sun_azimuth:d	72	0.000825	float
sun_elevation:d	72	0.000825	float
super_cooled_liquid_water:kgm2	72	0.000825	float
t_1000hPa:K	72	0.000825	float
total_cloud_cover:p	72	0.000825	float
visibility:m	72	0.000825	float
wind_speed_10m:ms	72	0.000825	float
wind_speed_u_10m:ms	72	0.000825	float
wind_speed_v_10m:ms	72	0.000825	float
wind_speed_w_1000hPa:ms	72	0.000825	float
y			float

	variable_type	special_types
absolute_humidity_2m:gm3	numeric	
air_density_2m:kgm3	numeric	
ceiling_height_agl:m	numeric	
clear_sky_energy_1h:J	numeric	
clear_sky_energy_1h:J_not_shifted	numeric	
clear_sky_rad:W	numeric	
cloud_base_agl:m	numeric	
dew_or_rime:idx	category	
dew_point_2m:K	numeric	
diffuse_rad:W	numeric	
diffuse_rad_1h:J	numeric	
diffuse_rad_1h:J_not_shifted	numeric	
direct_rad:W	numeric	
direct_rad_1h:J	numeric	
direct_rad_1h:J_not_shifted	numeric	
effective_cloud_cover:p	numeric	
elevation:m	category	
fresh_snow_12h:cm	numeric	
fresh_snow_12h:cm_not_shifted	numeric	
fresh_snow_1h:cm	numeric	
fresh_snow_1h:cm_not_shifted	numeric	
fresh_snow_24h:cm	numeric	
fresh_snow_24h:cm_not_shifted	numeric	
fresh_snow_3h:cm	numeric	

fresh_snow_3h:cm_not_shifted	numeric
fresh_snow_6h:cm	numeric
fresh_snow_6h:cm_not_shifted	numeric
is_day:idx	category
is_estimated	category
is_in_shadow:idx	category
location	category
msl_pressure:hPa	numeric
precip_5min:mm	numeric
precip_type_5min:idx	category
pressure_100m:hPa	numeric
pressure_50m:hPa	numeric
prob_rime:p	numeric
rain_water:kgm2	numeric
relative_humidity_1000hPa:p	numeric
sample_weight	category
sfc_pressure:hPa	numeric
snow_depth:cm	numeric
snow_melt_10min:mm	numeric
snow_water:kgm2	numeric
sun_azimuth:d	numeric
sun_elevation:d	numeric
super_cooled_liquid_water:kgm2	numeric
t_1000hPa:K	numeric
total_cloud_cover:p	numeric
visibility:m	numeric
wind_speed_10m:ms	numeric
wind_speed_u_10m:ms	numeric
wind_speed_v_10m:ms	numeric
wind_speed_w_1000hPa:ms	category
y	numeric

test_data dataset summary

	count	unique	top	freq	mean \
absolute_humidity_2m:gm3	5791	289			4.192639
air_density_2m:kgm3	5791	640			1.280018
ceiling_height_agl:m	4395	4247			3278.267059
clear_sky_energy_1h:J	5788	3059			469132.824948
clear_sky_energy_1h:J_not_shifted	5791	3059			468797.225142
clear_sky_rad:W	5791	2046			130.246477
cloud_base_agl:m	4934	4719			1733.271034
dew_or_rime:idx	5791	9			-0.033716
dew_point_2m:K	5791	948			270.733081
diffuse_rad:W	5791	2237			42.175259
diffuse_rad_1h:J	5788	3065			152461.828645
diffuse_rad_1h:J_not_shifted	5791	3065			152259.007684
direct_rad:W	5791	1829			51.829421
direct_rad_1h:J	5788	2676			186526.762509

direct_rad_1h:J_not_shifted	5791	2677			186384.946987
effective_cloud_cover:p	5791	2100			66.598541
elevation:m	5791	3			11.262131
fresh_snow_12h:cm	5788	82			0.415048
fresh_snow_12h:cm_not_shifted	5791	82			0.413935
fresh_snow_1h:cm	5788	23			0.032308
fresh_snow_1h:cm_not_shifted	5791	23			0.032171
fresh_snow_24h:cm	5788	108			0.808967
fresh_snow_24h:cm_not_shifted	5791	108			0.80594
fresh_snow_3h:cm	5788	42			0.100259
fresh_snow_3h:cm_not_shifted	5791	42			0.099724
fresh_snow_6h:cm	5788	60			0.204492
fresh_snow_6h:cm_not_shifted	5791	60			0.203626
is_day:idx	5791	5			0.488387
is_estimated	5791	1			1.0
is_in_shadow:idx	5791	5			0.555085
location	5791	3	A	2161	
msl_pressure:hPa	5791	2040			1012.678587
precip_5min:mm	5791	63			0.003687
precip_type_5min:idx	5791	12			0.086039
pressure_100m:hPa	5791	2124			998.781639
pressure_50m:hPa	5791	2134			1005.02648
prob_rime:p	5791	350			1.502776
rain_water:kgm2	5791	7			0.000984
relative_humidity_1000hPa:p	5791	2051			70.810205
sample_weight	5791	1			1.0
sfc_pressure:hPa	5791	2148			1011.29959
snow_depth:cm	5791	78			0.131661
snow_melt_10min:mm	5791	38			0.000695
snow_water:kgm2	5791	68			0.078393
sun_azimuth:d	5791	5681			179.475343
sun_elevation:d	5791	5093			-0.927197
super_cooled_liquid_water:kgm2	5791	31			0.035175
t_1000hPa:K	5791	825			275.185991
total_cloud_cover:p	5791	1838			71.785616
visibility:m	5791	5784			29884.461577
wind_speed_10m:ms	5791	424			3.227599
wind_speed_u_10m:ms	5791	672			0.668019
wind_speed_v_10m:ms	5791	483			0.538344
wind_speed_w_1000hPa:ms	5791	8			-0.000155
y	5791	2304			272.991992

	std	min	25% \
absolute_humidity_2m:gm3	1.300644	1.1	3.35
air_density_2m:kgm3	0.024372	1.219	1.26375
ceiling_height_agl:m	2590.751931	27.925	1149.0625
clear_sky_energy_1h:J	689638.596662	0.0	0.0
clear_sky_energy_1h:J_not_shifted	689490.588724	0.0	0.0

clear_sky_rad:W	191.578221	0.0	0.0
cloud_base_agl:m	1987.046511	27.5	525.4375
dew_or_rime:idx	0.233147	-1.0	0.0
dew_point_2m:K	4.634046	255.05	268.33749
diffuse_rad:W	59.158733	0.0	0.0
diffuse_rad_1h:J	211011.771342	0.0	0.0
diffuse_rad_1h:J_not_shifted	210855.943527	0.0	0.0
direct_rad:W	110.450287	0.0	0.0
direct_rad_1h:J	393513.65175	0.0	0.0
direct_rad_1h:J_not_shifted	393435.26945	0.0	0.0
effective_cloud_cover:p	37.583548	0.0	33.6375
elevation:m	7.8114	6.0	6.0
fresh_snow_12h:cm	1.240733	0.0	0.0
fresh_snow_12h:cm_not_shifted	1.239777	0.0	0.0
fresh_snow_1h:cm	0.170919	0.0	0.0
fresh_snow_1h:cm_not_shifted	0.170652	0.0	0.0
fresh_snow_24h:cm	1.982565	0.0	0.0
fresh_snow_24h:cm_not_shifted	1.977015	0.0	0.0
fresh_snow_3h:cm	0.425766	0.0	0.0
fresh_snow_3h:cm_not_shifted	0.424781	0.0	0.0
fresh_snow_6h:cm	0.738932	0.0	0.0
fresh_snow_6h:cm_not_shifted	0.73781	0.0	0.0
is_day:idx	0.486436	0.0	0.0
is_estimated	0.0	1.0	1.0
is_in_shadow:idx	0.483636	0.0	0.0
location			
msl_pressure:hPa	13.953847	975.3	1003.875
precip_5min:mm	0.017701	0.0	0.0
precip_type_5min:idx	0.393918	0.0	0.0
pressure_100m:hPa	13.825369	962.4	989.9
pressure_50m:hPa	13.873049	968.45	996.087475
prob_rime:p	7.839203	0.0	0.0
rain_water:kgm2	0.009596	0.0	0.0
relative_humidity_1000hPa:p	14.940249	21.325	60.75
sample_weight	0.0	1.0	1.0
sfc_pressure:hPa	13.921629	974.55	1002.25
snow_depth:cm	0.635847	0.0	0.0
snow_melt_10min:mm	0.007333	0.0	0.0
snow_water:kgm2	0.189057	0.0	0.0
sun_azimuth:d	96.891969	14.913	94.264625
sun_elevation:d	20.775858	-44.28175	-17.109625
super_cooled_liquid_water:kgm2	0.084895	0.0	0.0
t_1000hPa:K	3.823552	261.975	272.8
total_cloud_cover:p	37.578218	0.0	41.8
visibility:m	14669.627165	1215.4	18727.05
wind_speed_10m:ms	1.869023	0.05	1.725
wind_speed_u_10m:ms	3.12501	-7.15	-1.75
wind_speed_v_10m:ms	1.838513	-5.3	-0.8

wind_speed_w_1000hPa:ms	0.005234	-0.1	0.0
y	770.841016	-0.0	0.0

	50%	75%	max	dtypes \
absolute_humidity_2m:gm3	4.3	5.05	7.7	float64
air_density_2m:kgm3	1.279	1.29375	1.37175	float64
ceiling_height_agl:m	2618.95	4661.025	12294.901	float64
clear_sky_energy_1h:J	11008.5	791394.0	2554290.5	float64
clear_sky_energy_1h:J_not_shifted	10525.3	789350.65	2554290.5	float64
clear_sky_rad:W	2.675	221.925	710.5	float64
cloud_base_agl:m	904.825	2014.962525	10674.3	float64
dew_or_rime:idx	0.0	0.0	1.0	float64
dew_point_2m:K	271.6	273.9	280.4	float64
diffuse_rad:W	1.775	78.4875	311.95	float64
diffuse_rad_1h:J	18860.9	279202.425	1071799.5	float64
diffuse_rad_1h:J_not_shifted	18852.8	278503.35	1071799.5	float64
direct_rad:W	0.0	34.0875	530.15	float64
direct_rad_1h:J	0.0	129529.5	1895533.0	float64
direct_rad_1h:J_not_shifted	0.0	128914.1	1895533.0	float64
effective_cloud_cover:p	85.375	99.975	100.0	float64
elevation:m	7.0	24.0	24.0	float64
fresh_snow_12h:cm	0.0	0.0	9.5	float64
fresh_snow_12h:cm_not_shifted	0.0	0.0	9.5	float64
fresh_snow_1h:cm	0.0	0.0	2.6	float64
fresh_snow_1h:cm_not_shifted	0.0	0.0	2.6	float64
fresh_snow_24h:cm	0.0	0.2	14.8	float64
fresh_snow_24h:cm_not_shifted	0.0	0.2	14.8	float64
fresh_snow_3h:cm	0.0	0.0	5.2	float64
fresh_snow_3h:cm_not_shifted	0.0	0.0	5.2	float64
fresh_snow_6h:cm	0.0	0.0	7.5	float64
fresh_snow_6h:cm_not_shifted	0.0	0.0	7.5	float64
is_day:idx	0.25	1.0	1.0	float64
is_estimated	1.0	1.0	1.0	int64
is_in_shadow:idx	1.0	1.0	1.0	float64
location				object
msl_pressure:hPa	1011.625	1023.8125	1041.3501	float64
precip_5min:mm	0.0	0.0	0.2475	float64
precip_type_5min:idx	0.0	0.0	3.0	float64
pressure_100m:hPa	997.9	1009.875	1028.05	float64
pressure_50m:hPa	1004.1	1016.1625	1034.45	float64
prob_rime:p	0.0	0.0	91.875	float64
rain_water:kgm2	0.0	0.0	0.175	float64
relative_humidity_1000hPa:p	73.1	82.075	98.0	float64
sample_weight	1.0	1.0	1.0	int64
sfc_pressure:hPa	1010.35	1022.5125	1040.8501	float64
snow_depth:cm	0.0	0.0	4.9	float64
snow_melt_10min:mm	0.0	0.0	0.14	float64
snow_water:kgm2	0.0	0.1	2.15	float64

sun_azimuth:d	179.52899	263.49875	347.37848	float64
sun_elevation:d	-0.79825	15.30325	41.13025	float64
super_cooled_liquid_water:kgm2	0.0	0.0	0.75	float64
t_1000hPa:K	275.175	277.525	285.1	float64
total_cloud_cover:p	96.65	100.0	100.0	float64
visibility:m	31311.025	40438.6635	66178.45	float64
wind_speed_10m:ms	2.9	4.45	10.2	float64
wind_speed_u_10m:ms	0.3	2.9	9.95	float64
wind_speed_v_10m:ms	0.625	1.825	7.15	float64
wind_speed_w_1000hPa:ms	0.0	0.0	0.1	float64
y	0.0	142.906699	5172.64	float64

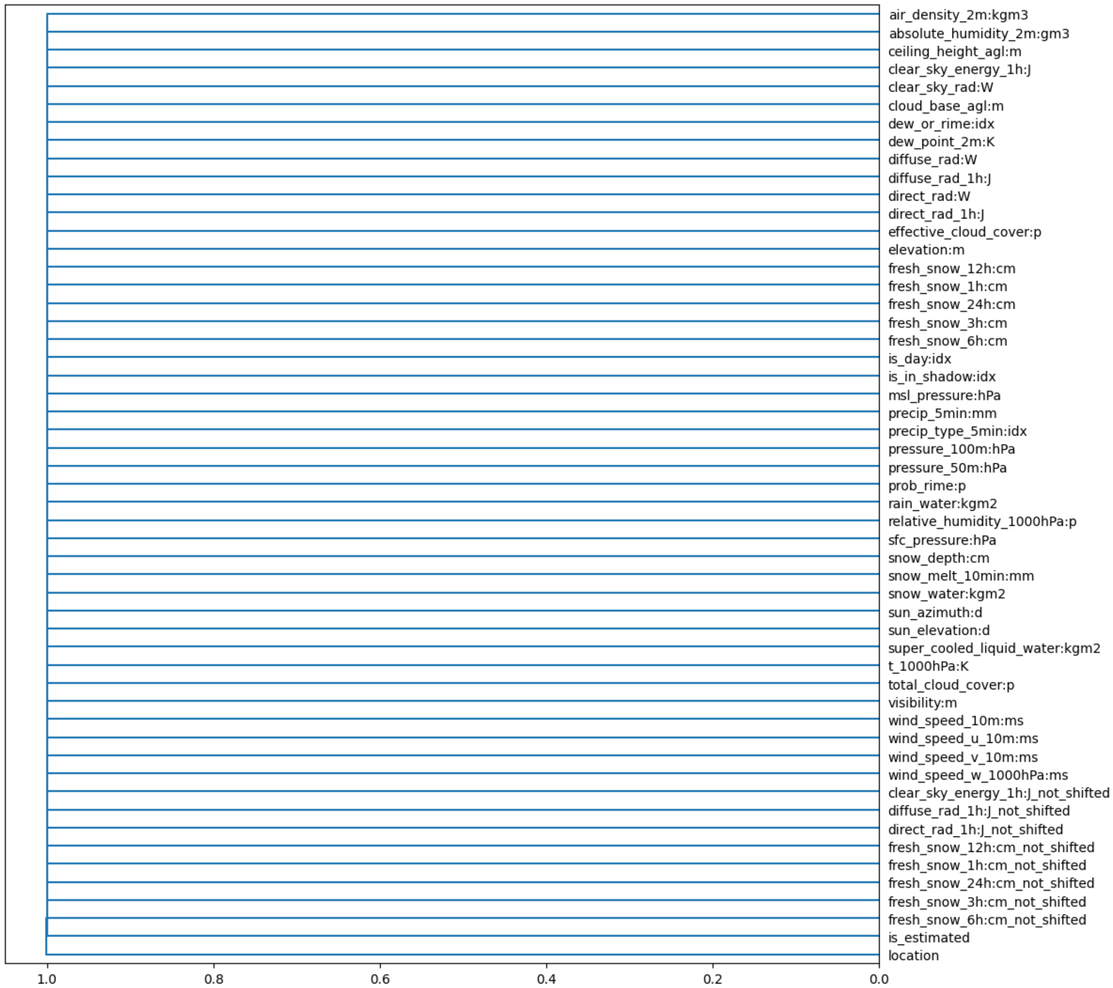
	missing_count	missing_ratio	raw_type \
absolute_humidity_2m:gm3			float
air_density_2m:kgm3			float
ceiling_height_agl:m	1396	0.241064	float
clear_sky_energy_1h:J	3	0.000518	float
clear_sky_energy_1h:J_not_shifted			float
clear_sky_rad:W			float
cloud_base_agl:m	857	0.147988	float
dew_or_rime:idx			float
dew_point_2m:K			float
diffuse_rad:W			float
diffuse_rad_1h:J	3	0.000518	float
diffuse_rad_1h:J_not_shifted			float
direct_rad:W			float
direct_rad_1h:J	3	0.000518	float
direct_rad_1h:J_not_shifted			float
effective_cloud_cover:p			float
elevation:m			float
fresh_snow_12h:cm	3	0.000518	float
fresh_snow_12h:cm_not_shifted			float
fresh_snow_1h:cm	3	0.000518	float
fresh_snow_1h:cm_not_shifted			float
fresh_snow_24h:cm	3	0.000518	float
fresh_snow_24h:cm_not_shifted			float
fresh_snow_3h:cm	3	0.000518	float
fresh_snow_3h:cm_not_shifted			float
fresh_snow_6h:cm	3	0.000518	float
fresh_snow_6h:cm_not_shifted			float
is_day:idx			float
is_estimated			int
is_in_shadow:idx			float
location			object
msl_pressure:hPa			float
precip_5min:mm			float
precip_type_5min:idx			float
pressure_100m:hPa			float

pressure_50m:hPa	float
prob_rime:p	float
rain_water:kgm2	float
relative_humidity_1000hPa:p	float
sample_weight	int
sfc_pressure:hPa	float
snow_depth:cm	float
snow_melt_10min:mm	float
snow_water:kgm2	float
sun_azimuth:d	float
sun_elevation:d	float
super_cooled_liquid_water:kgm2	float
t_1000hPa:K	float
total_cloud_cover:p	float
visibility:m	float
wind_speed_10m:ms	float
wind_speed_u_10m:ms	float
wind_speed_v_10m:ms	float
wind_speed_w_1000hPa:ms	float
y	float

	variable_type	special_types
absolute_humidity_2m:gm3	numeric	
air_density_2m:kgm3	numeric	
ceiling_height_agl:m	numeric	
clear_sky_energy_1h:J	numeric	
clear_sky_energy_1h:J_not_shifted	numeric	
clear_sky_rad:W	numeric	
cloud_base_agl:m	numeric	
dew_or_rime:idx	category	
dew_point_2m:K	numeric	
diffuse_rad:W	numeric	
diffuse_rad_1h:J	numeric	
diffuse_rad_1h:J_not_shifted	numeric	
direct_rad:W	numeric	
direct_rad_1h:J	numeric	
direct_rad_1h:J_not_shifted	numeric	
effective_cloud_cover:p	numeric	
elevation:m	category	
fresh_snow_12h:cm	numeric	
fresh_snow_12h:cm_not_shifted	numeric	
fresh_snow_1h:cm	numeric	
fresh_snow_1h:cm_not_shifted	numeric	
fresh_snow_24h:cm	numeric	
fresh_snow_24h:cm_not_shifted	numeric	
fresh_snow_3h:cm	numeric	
fresh_snow_3h:cm_not_shifted	numeric	
fresh_snow_6h:cm	numeric	

fresh_snow_6h:cm_not_shifted	numeric
is_day:idx	category
is_estimated	category
is_in_shadow:idx	category
location	category
msl_pressure:hPa	numeric
precip_5min:mm	numeric
precip_type_5min:idx	category
pressure_100m:hPa	numeric
pressure_50m:hPa	numeric
prob_rime:p	numeric
rain_water:kgm2	category
relative_humidity_1000hPa:p	numeric
sample_weight	category
sfc_pressure:hPa	numeric
snow_depth:cm	numeric
snow_melt_10min:mm	numeric
snow_water:kgm2	numeric
sun_azimuth:d	numeric
sun_elevation:d	numeric
super_cooled_liquid_water:kgm2	numeric
t_1000hPa:K	numeric
total_cloud_cover:p	numeric
visibility:m	numeric
wind_speed_10m:ms	numeric
wind_speed_u_10m:ms	numeric
wind_speed_v_10m:ms	numeric
wind_speed_w_1000hPa:ms	category
y	numeric

1.0.1 Feature Distance

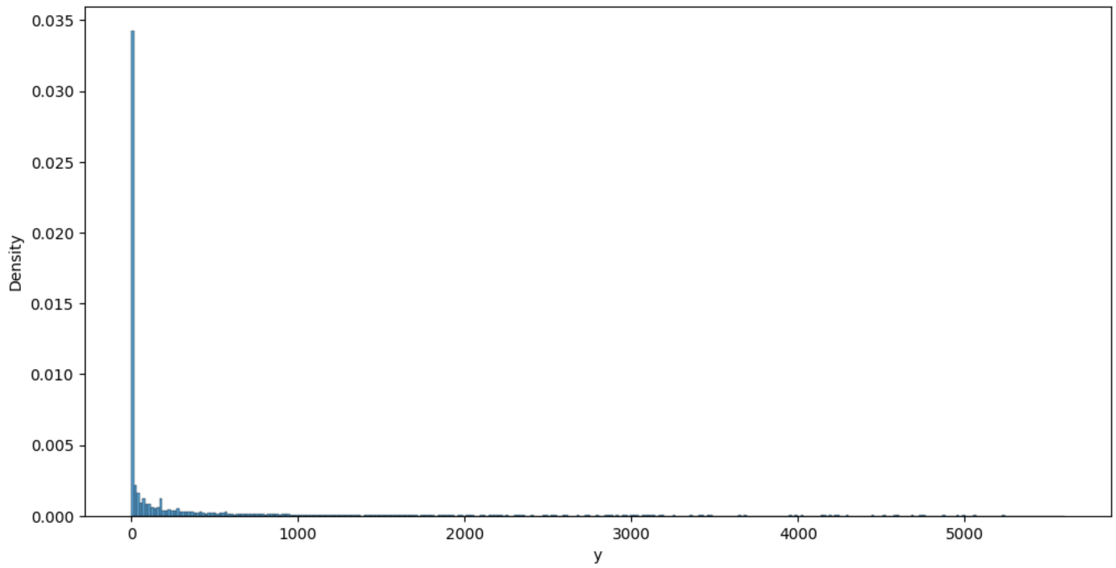


[6]:
```python
if run_analysis:
    auto.target_analysis(train_data=train_data, label="y")
```

1.1 Target variable analysis

```
   count        mean         std  min  25%  50%       75%      max   dtypes  \
y  10000  299.128516  787.495283  0.0  0.0  0.0  183.7125  5596.36  float64

   unique missing_count missing_ratio raw_type special_types
y    2419                                 float
```

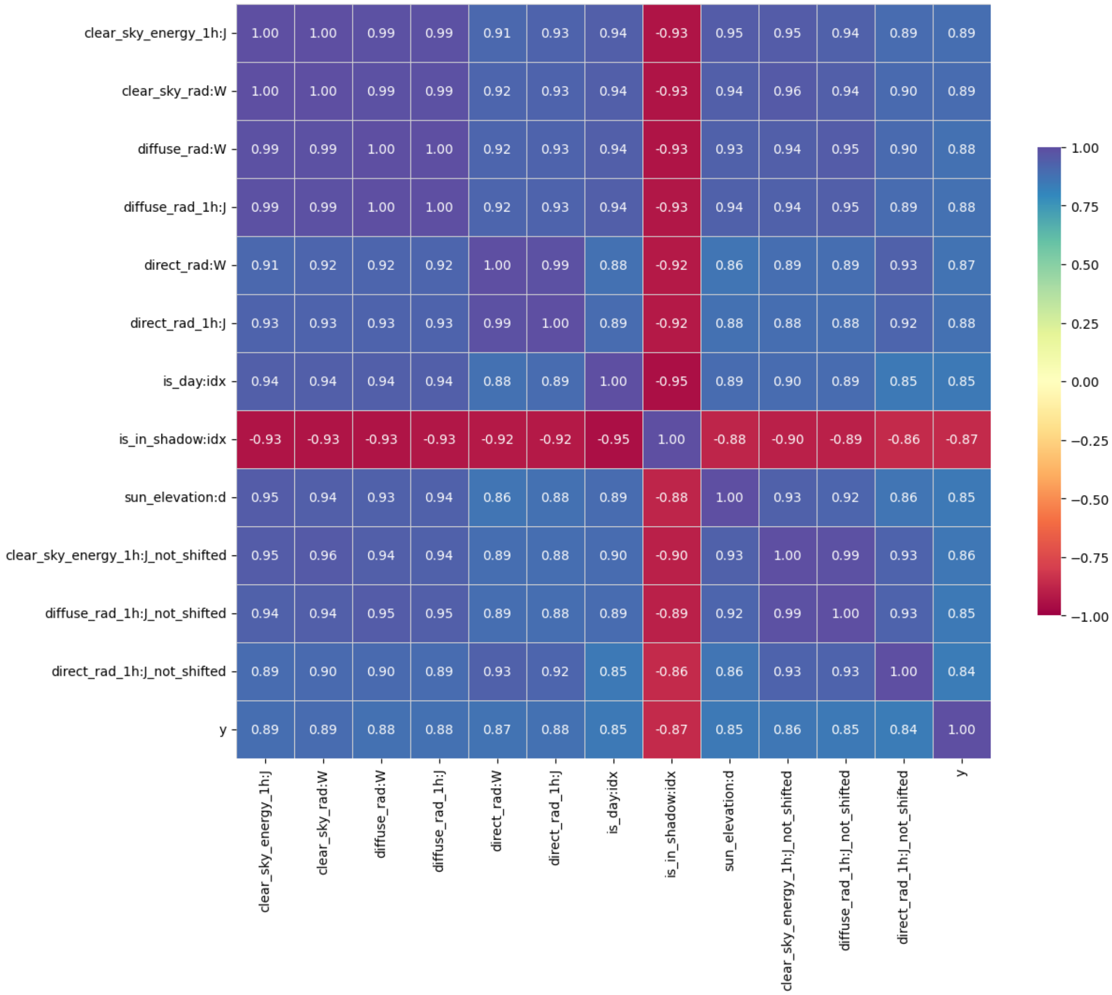


1.1.1 Distribution fits for target variable

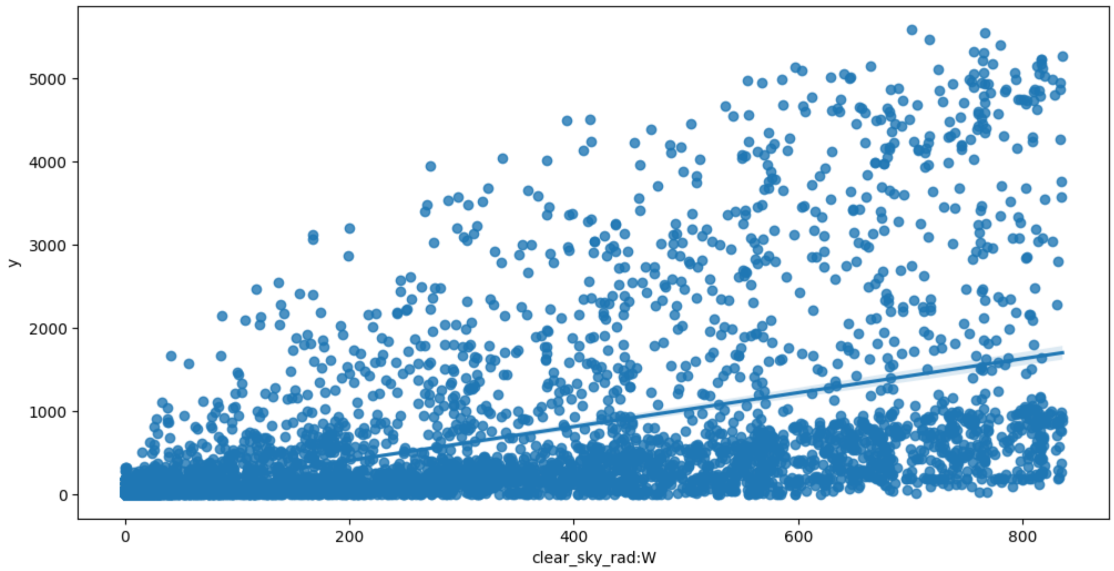
- none of the attempted distribution fits satisfy specified minimum p-value threshold: `0.01`

1.1.2 Target variable correlations

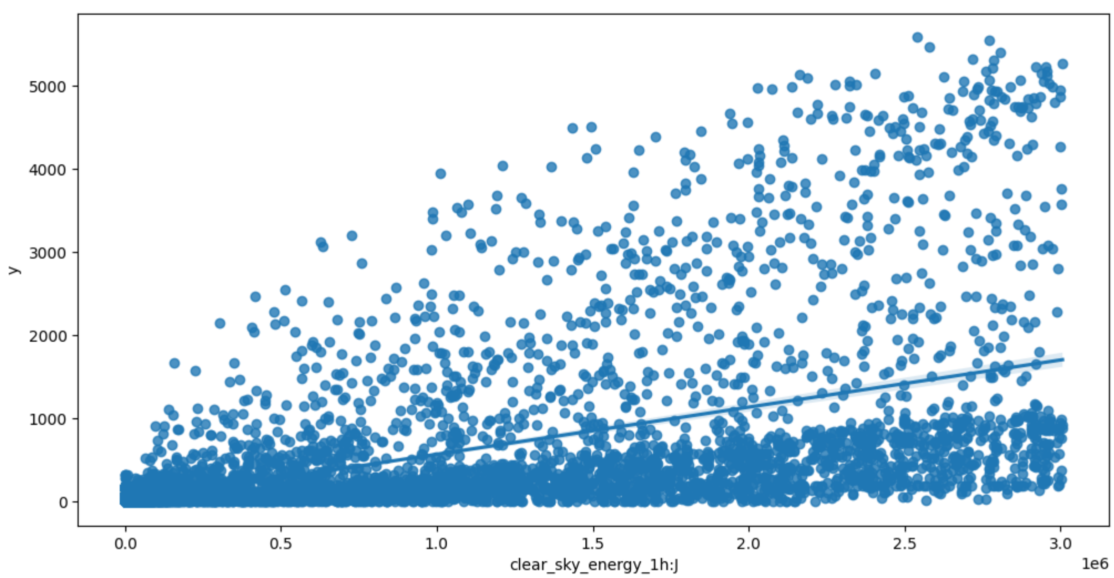
`train_data` - `spearman` correlation matrix; focus: absolute correlation for `y` >= `0.5` (sample size: 10000)



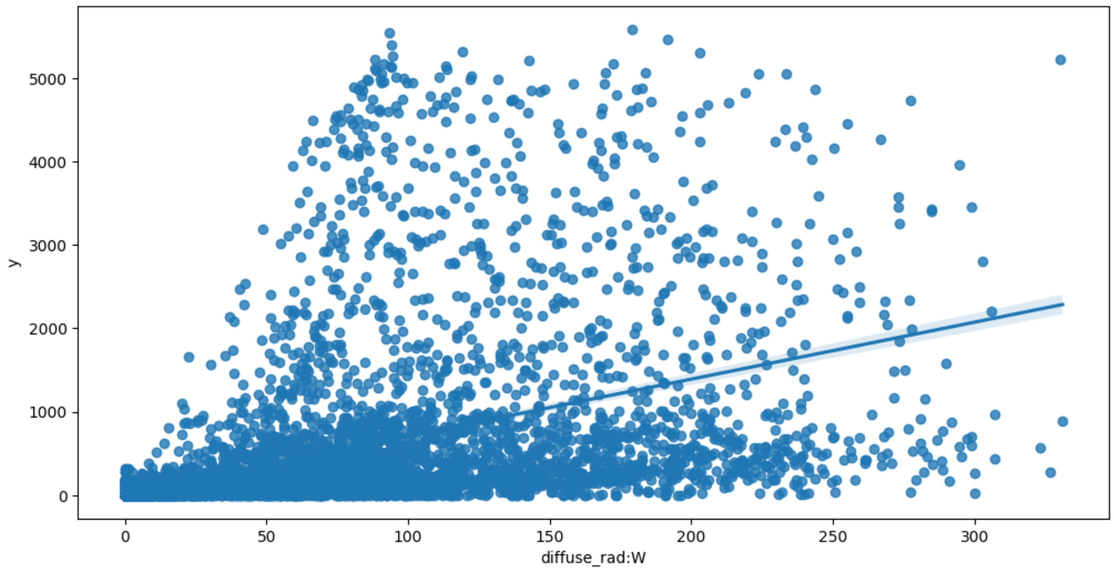
Feature interaction between `clear_sky_rad:W`/`y` in `train_data` (sample size: 10000)



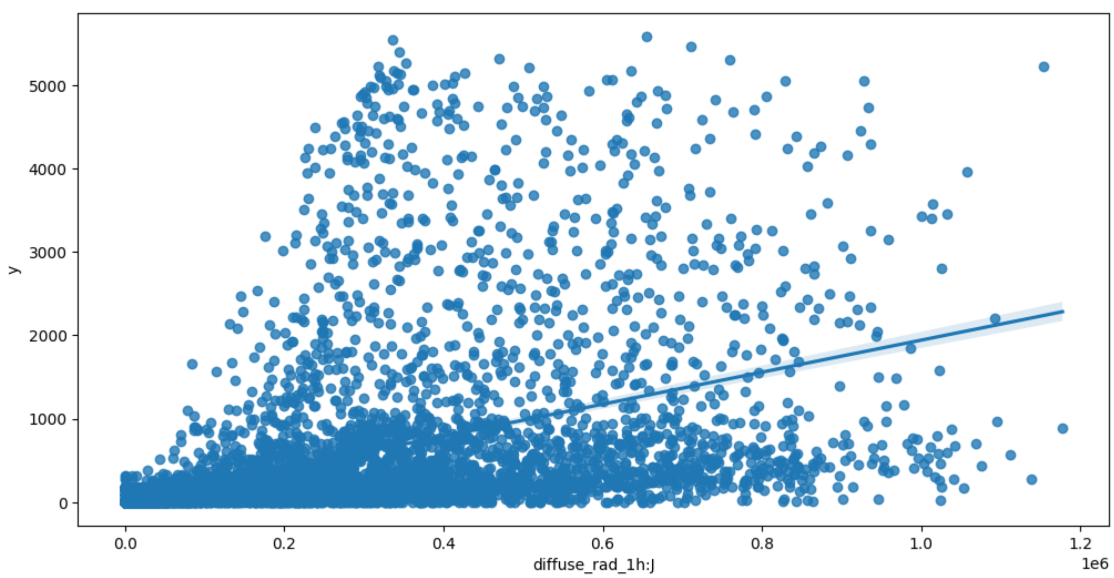
Feature interaction between `clear_sky_energy_1h:J/y` in `train_data` (sample size: 10000)



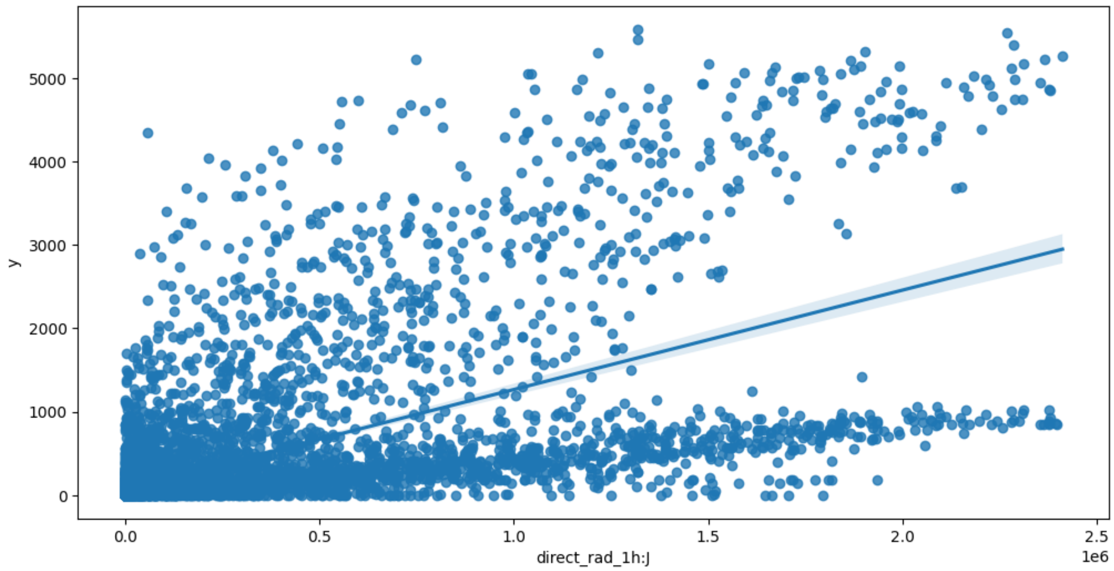
Feature interaction between `diffuse_rad:W/y` in `train_data` (sample size: 10000)



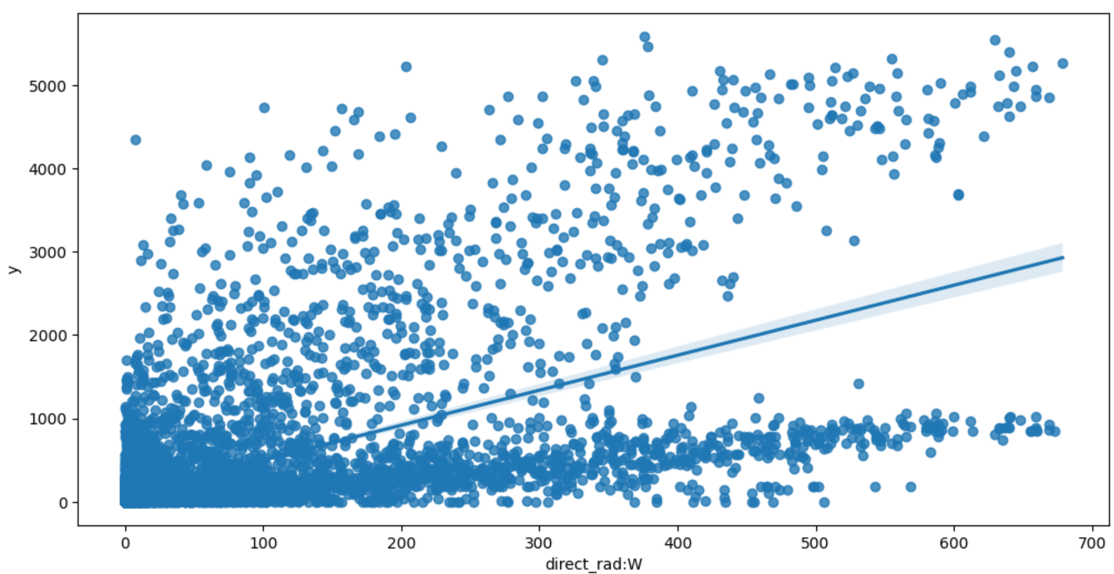
Feature interaction between `diffuse_rad_1h:J/y` in `train_data` (sample size: 10000)



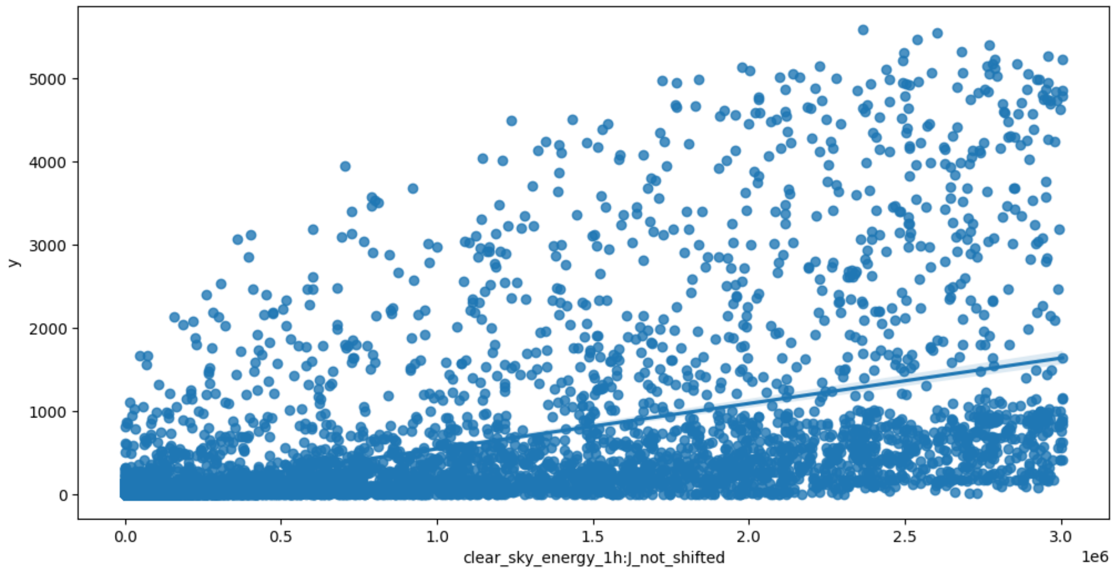
Feature interaction between `direct_rad_1h:J/y` in `train_data` (sample size: 10000)



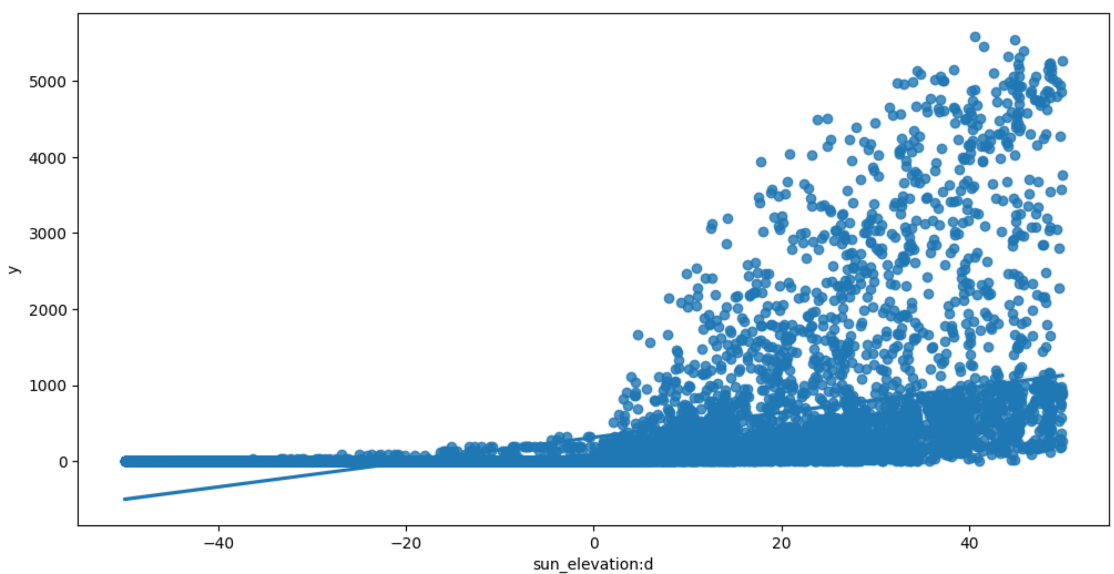
Feature interaction between `direct_rad:W/y` in `train_data` (sample size: 10000)



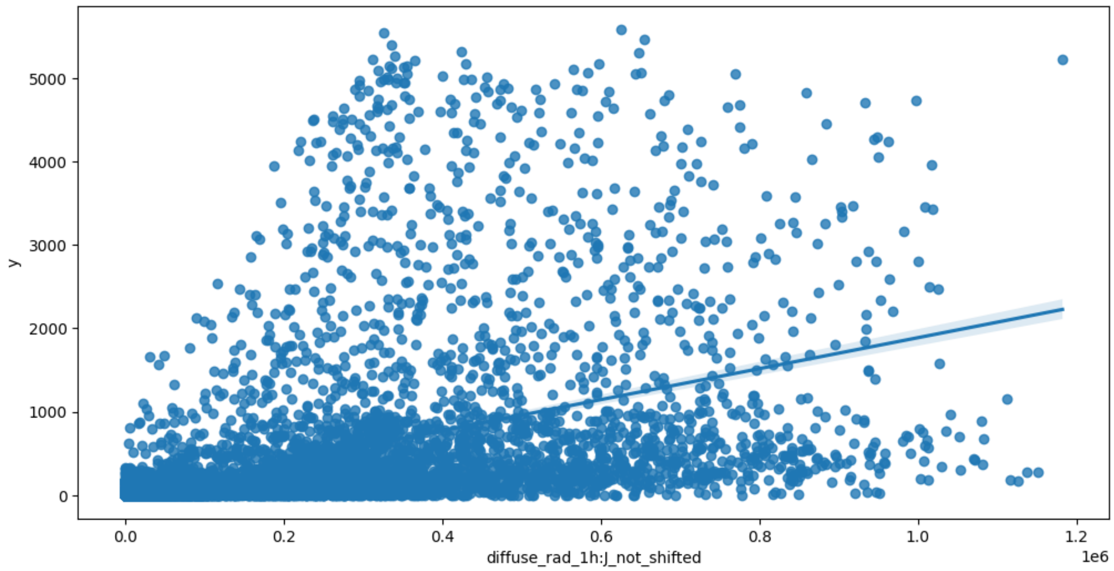
Feature interaction between `clear_sky_energy_1h:J_not_shifted/y` in `train_data` (sample size: 10000)



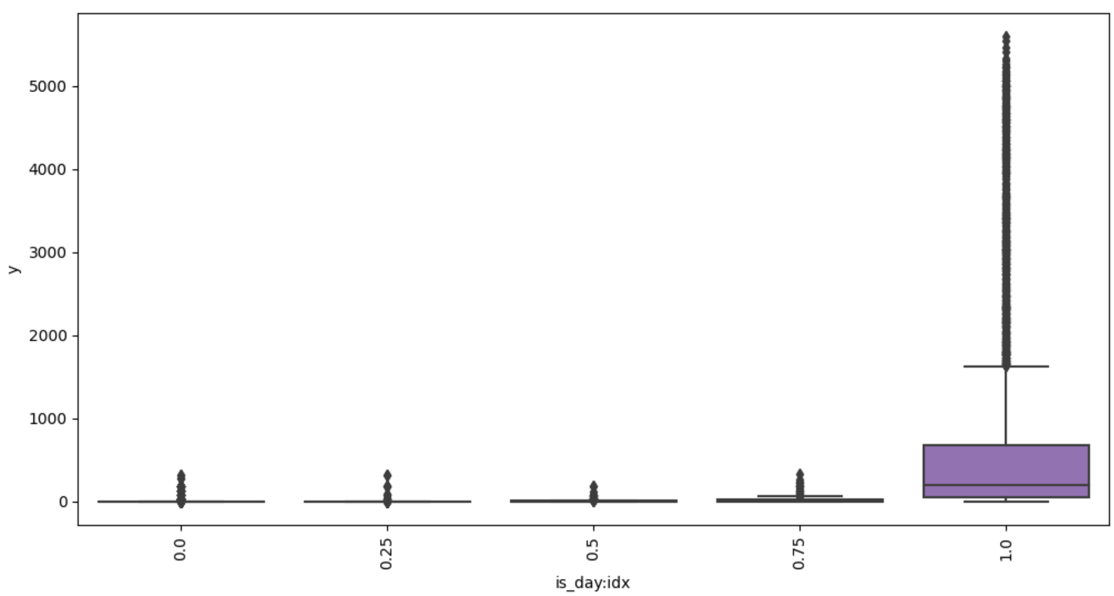
Feature interaction between `sun_elevation:d/y` in `train_data` (sample size: 10000)



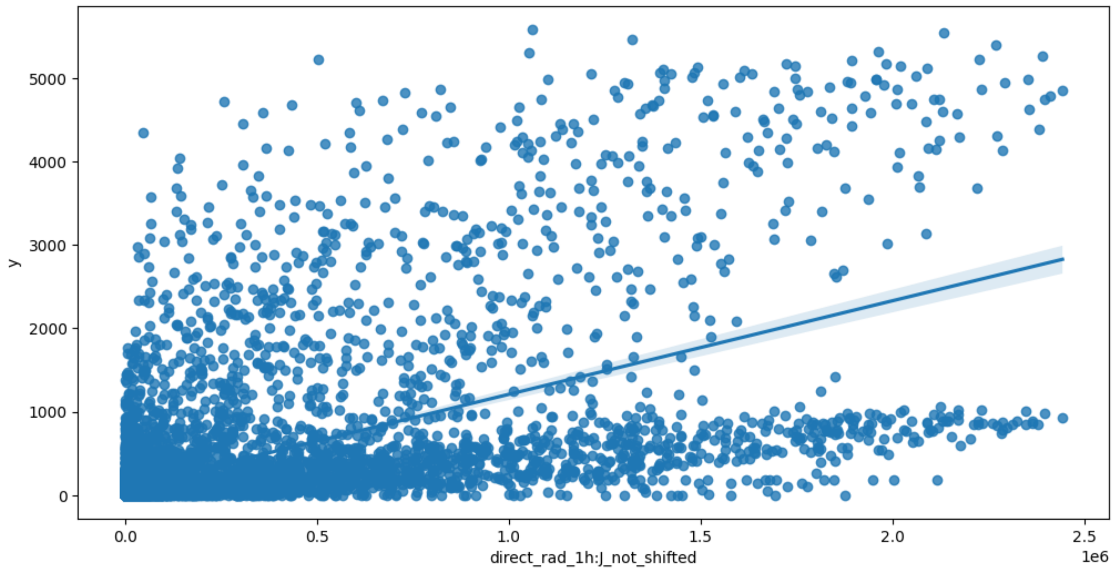
Feature interaction between `diffuse_rad_1h:J_not_shifted/y` in `train_data` (sample size: 10000)



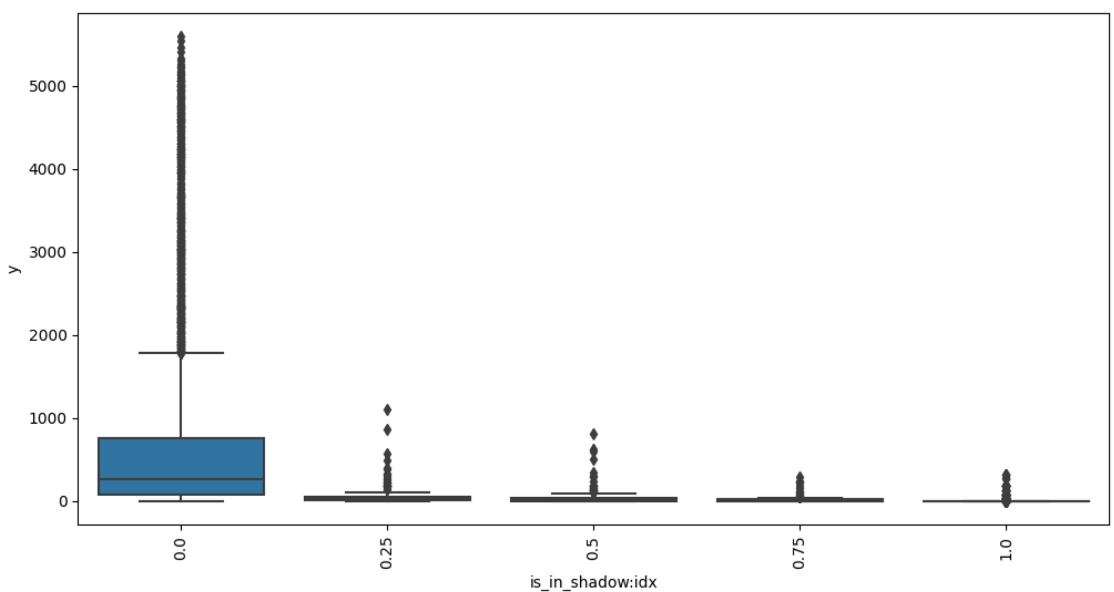
Feature interaction between `is_day:idx/y` in `train_data` (sample size: 10000)



Feature interaction between `direct_rad_1h:J_not_shifted/y` in `train_data` (sample size: 10000)



Feature interaction between `is_in_shadow:idx/y` in `train_data` (sample size: 10000)



2 Starting

[7]:
```python
import os
```

```
# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 88
Now creating submission number: 89
New filename: submission_89
```

[8]:
```
predictors = [None, None, None]
```

[9]:
```
def fit_predictor_for_location(loc):
    print(f"Training model for location {loc}...")
    # sum of sample weights for this location, and number of rows, for both␣
↪train and tune data and test data
    print("Train data sample weight sum:", train_data[train_data["location"] ==␣
↪loc]["sample_weight"].sum())
    print("Train data number of rows:", train_data[train_data["location"] ==␣
↪loc].shape[0])
    if use_tune_data:
        print("Tune data sample weight sum:",␣
↪tuning_data[tuning_data["location"] == loc]["sample_weight"].sum())
        print("Tune data number of rows:", tuning_data[tuning_data["location"]␣
↪== loc].shape[0])
    if use_test_data:
        print("Test data sample weight sum:", test_data[test_data["location"]␣
↪== loc]["sample_weight"].sum())
        print("Test data number of rows:", test_data[test_data["location"] ==␣
↪loc].shape[0])
    predictor = TabularPredictor(
        label=label,
        eval_metric=metric,
        path=f"AutogluonModels/{new_filename}_{loc}",
        sample_weight=sample_weight,
        weight_evaluation=weight_evaluation,
        groups="group" if use_groups else None,
    ).fit(
```

```
        train_data=train_data[train_data["location"] == loc],
        time_limit=time_limit,
        presets=presets,
        num_stack_levels=num_stack_levels,
        num_bag_folds=num_bag_folds if not use_groups else 2,# just put␣
↪somethin, will be overwritten anyways
        tuning_data=tuning_data[tuning_data["location"] == loc] if␣
↪use_tune_data else None,
        use_bag_holdout=use_bag_holdout,
        holdout_frac=holdout_frac,
    )

    # evaluate on test data
    if use_test_data:
        # drop sample_weight column
        t = test_data[test_data["location"] == loc]#.
↪drop(columns=["sample_weight"])
        perf = predictor.evaluate(t)
        print("Evaluation on test data:")
        print(perf[predictor.eval_metric.name])

    return predictor

loc = "A"
predictors[0] = fit_predictor_for_location(loc)
```

```
Warning: path already exists! This predictor may overwrite an existing
predictor! path="AutogluonModels/submission_89_A"
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 300s
AutoGluon will save models to "AutogluonModels/submission_89_A/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   307.40 GB / 315.93 GB (97.3%)
Train Data Rows:    31924
Train Data Columns: 54
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 632.68576,
1165.32372)
```

```
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    132022.96 MB
        Train Data (Original)  Memory Usage: 15.39 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:

Training model for location A…
Train data sample weight sum: 31924
Train data number of rows: 31924
Test data sample weight sum: 2161
Test data number of rows: 2161

                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['sample_weight', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 51 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 50 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', ['bool']) :  2 | ['elevation:m', 'is_estimated']
        0.2s = Fit runtime
        52 features in original data used to generate 52 features in processed
data.
        Train Data (Processed) Memory Usage: 12.83 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.22s …
```

```
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 199.8s of the
299.77s of remaining time.
        -219.613         = Validation score   (-mean_absolute_error)
        0.05s    = Training   runtime
        1.17s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 198.48s of the
298.45s of remaining time.
        -219.6317        = Validation score   (-mean_absolute_error)
        0.05s    = Training   runtime
        0.46s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 197.86s of the
297.83s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -155.6317        = Validation score   (-mean_absolute_error)
        42.62s   = Training   runtime
        17.07s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 147.4s of the
247.38s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
```

```
ParallelLocalFoldFittingStrategy
        -164.9935        = Validation score   (-mean_absolute_error)
        51.56s   = Training   runtime
        16.2s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 92.14s of the
192.12s of remaining time.
        -180.6119        = Validation score   (-mean_absolute_error)
        11.32s   = Training   runtime
        1.3s     = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 77.44s of the
177.41s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -174.1327        = Validation score   (-mean_absolute_error)
        62.05s   = Training   runtime
        0.09s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 14.29s of the
114.26s of remaining time.
        -181.9104        = Validation score   (-mean_absolute_error)
        2.52s    = Training   runtime
        1.32s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 8.39s of the
108.37s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -216.5736        = Validation score   (-mean_absolute_error)
        7.69s    = Training   runtime
        0.73s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 299.78s of the
99.54s of remaining time.
        -155.0187        = Validation score   (-mean_absolute_error)
        0.6s     = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 98.92s of the
98.9s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -156.8064        = Validation score   (-mean_absolute_error)
        2.84s    = Training   runtime
        0.17s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 94.19s of the 94.18s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -155.1538        = Validation score   (-mean_absolute_error)
        2.38s    = Training   runtime
```

```
        0.08s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 90.45s of the
90.44s of remaining time.
        -153.7704        = Validation score   (-mean_absolute_error)
        15.51s   = Training   runtime
        1.51s    = Validation runtime
Fitting model: CatBoost_BAG_L2 … Training model for up to 71.38s of the 71.36s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -154.4355        = Validation score   (-mean_absolute_error)
        5.99s    = Training   runtime
        0.04s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L2 … Training model for up to 64.12s of the
64.1s of remaining time.
        -152.7918        = Validation score   (-mean_absolute_error)
        2.82s    = Training   runtime
        1.37s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L2 … Training model for up to 57.86s of the
57.85s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -153.6223        = Validation score   (-mean_absolute_error)
        41.82s   = Training   runtime
        0.73s    = Validation runtime
Fitting model: XGBoost_BAG_L2 … Training model for up to 14.73s of the 14.72s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -153.833         = Validation score   (-mean_absolute_error)
        2.96s    = Training   runtime
        0.13s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L2 … Training model for up to 10.41s of the
10.39s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -160.3937        = Validation score   (-mean_absolute_error)
        9.85s    = Training   runtime
        0.67s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 299.78s of the
-0.85s of remaining time.
        -151.0503        = Validation score   (-mean_absolute_error)
        0.58s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 301.48s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
```

```
TabularPredictor.load("AutogluonModels/submission_89_A/")
Evaluation: mean_absolute_error on test data: -189.0870959744424
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -189.0870959744424,
    "root_mean_squared_error": -424.2306549554531,
    "mean_squared_error": -179971.64860393267,
    "r2": 0.8694190903973649,
    "pearsonr": 0.934134287991857,
    "median_absolute_error": -4.977496242523193
}

Evaluation on test data:
-189.0870959744424
```

[10]:
```
loc = "B"
predictors[1] = fit_predictor_for_location(loc)
```

```
Warning: path already exists! This predictor may overwrite an existing
predictor! path="AutogluonModels/submission_89_B"
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 300s
AutoGluon will save models to "AutogluonModels/submission_89_B/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   307.44 GB / 315.93 GB (97.3%)
Train Data Rows:    30792
Train Data Columns: 54
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 97.67477, 195.03642)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    130628.99 MB
        Train Data (Original)  Memory Usage: 14.84 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
```

```
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:

Training model for location B…
Train data sample weight sum: 30792
Train data number of rows: 30792
Test data sample weight sum: 2051
Test data number of rows: 2051

                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['sample_weight', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 51 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 50 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', ['bool']) :  2 | ['elevation:m', 'is_estimated']
        0.2s = Fit runtime
        52 features in original data used to generate 52 features in processed
data.
        Train Data (Processed) Memory Usage: 12.38 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.28s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
```

```
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 199.76s of the
299.72s of remaining time.
        -47.1734         = Validation score   (-mean_absolute_error)
        0.05s    = Training   runtime
        0.47s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 199.18s of the
299.13s of remaining time.
        -47.0004         = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.45s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 198.63s of the
298.59s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -28.7015         = Validation score   (-mean_absolute_error)
        45.34s   = Training   runtime
        19.33s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 149.22s of the
249.18s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -30.3689         = Validation score   (-mean_absolute_error)
        51.94s   = Training   runtime
        19.44s   = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 93.45s of the
193.41s of remaining time.
        -34.9439         = Validation score   (-mean_absolute_error)
        12.78s   = Training   runtime
        1.27s    = Validation runtime
```

```
Fitting model: CatBoost_BAG_L1 … Training model for up to 78.86s of the
178.81s of remaining time.
	Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
	-33.6817	 = Validation score   (-mean_absolute_error)
	63.78s	 = Training   runtime
	0.07s	 = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 13.89s of the
113.85s of remaining time.
	-36.0229	 = Validation score   (-mean_absolute_error)
	2.39s	 = Training   runtime
	1.26s	 = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 9.67s of the
109.62s of remaining time.
	Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
	-43.6085	 = Validation score   (-mean_absolute_error)
	9.54s	 = Training   runtime
	0.76s	 = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 299.72s of the
98.83s of remaining time.
	-28.5421	 = Validation score   (-mean_absolute_error)
	0.59s	 = Training   runtime
	0.0s	 = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 98.23s of the
98.21s of remaining time.
	Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
	-26.1364	 = Validation score   (-mean_absolute_error)
	4.99s	 = Training   runtime
	0.35s	 = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 91.89s of the 91.87s
of remaining time.
	Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
	-25.7381	 = Validation score   (-mean_absolute_error)
	3.31s	 = Training   runtime
	0.11s	 = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 87.26s of the
87.25s of remaining time.
	-24.5054	 = Validation score   (-mean_absolute_error)
	15.17s	 = Training   runtime
	1.32s	 = Validation runtime
Fitting model: CatBoost_BAG_L2 … Training model for up to 70.23s of the 70.22s
of remaining time.
	Fitting 8 child models (S1F1 - S1F8) | Fitting with
```

```
ParallelLocalFoldFittingStrategy
        -25.7772         = Validation score   (-mean_absolute_error)
        10.57s   = Training   runtime
        0.04s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L2 … Training model for up to 58.47s of the
58.46s of remaining time.
        -24.4516         = Validation score   (-mean_absolute_error)
        2.63s    = Training   runtime
        1.42s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L2 … Training model for up to 53.85s of the
53.84s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -24.9852         = Validation score   (-mean_absolute_error)
        40.3s    = Training   runtime
        0.73s    = Validation runtime
Fitting model: XGBoost_BAG_L2 … Training model for up to 12.18s of the 12.17s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -25.3105         = Validation score   (-mean_absolute_error)
        3.52s    = Training   runtime
        0.14s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L2 … Training model for up to 7.2s of the
7.19s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -31.2335         = Validation score   (-mean_absolute_error)
        7.33s    = Training   runtime
        0.68s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 299.72s of the
-1.57s of remaining time.
        -24.2899         = Validation score   (-mean_absolute_error)
        0.6s     = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 302.23s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_89_B/")
Evaluation: mean_absolute_error on test data: -36.70692390951731
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -36.70692390951731,
    "root_mean_squared_error": -88.26733573190592,
    "mean_squared_error": -7791.122557208996,
```

```
    "r2": 0.749414393838681,
    "pearsonr": 0.8834082340709369,
    "median_absolute_error": -5.018582344055176
}

Evaluation on test data:
-36.70692390951731
```

[11]:
```
loc = "C"
predictors[2] = fit_predictor_for_location(loc)
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 300s
AutoGluon will save models to "AutogluonModels/submission_89_C/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   305.77 GB / 315.93 GB (96.8%)
Train Data Rows:    24516
Train Data Columns: 54
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
        Label info (max, min, mean, stddev): (999.6, 0.0, 78.04527, 167.43618)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    129143.0 MB
        Train Data (Original)  Memory Usage: 11.82 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
```

```
Training model for location C…
Train data sample weight sum: 24516
Train data number of rows: 24516
Test data sample weight sum: 1579
Test data number of rows: 1579
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['sample_weight', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 51 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 50 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', ['bool']) :  2 | ['elevation:m', 'is_estimated']
        0.2s = Fit runtime
        52 features in original data used to generate 52 features in processed
data.
        Train Data (Processed) Memory Usage: 9.86 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.26s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
```

```
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 199.78s of the
299.74s of remaining time.
        -25.9293         = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.32s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 199.38s of the
299.34s of remaining time.
        -25.879  = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.31s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 198.98s of the
298.95s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -16.9668         = Validation score   (-mean_absolute_error)
        40.0s    = Training   runtime
        9.99s    = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 156.22s of the
256.18s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -18.1061         = Validation score   (-mean_absolute_error)
        50.33s   = Training   runtime
        9.92s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 103.18s of
the 203.15s of remaining time.
        -19.9705         = Validation score   (-mean_absolute_error)
        7.19s    = Training   runtime
        0.96s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 94.69s of the
194.65s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -18.9437         = Validation score   (-mean_absolute_error)
        76.46s   = Training   runtime
        0.07s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 17.04s of the
117.0s of remaining time.
        -20.0336         = Validation score   (-mean_absolute_error)
```

```
        1.6s     = Training   runtime
        0.94s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 14.12s of the
114.08s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -22.0753         = Validation score   (-mean_absolute_error)
        13.15s   = Training   runtime
        0.58s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 299.74s of the
99.63s of remaining time.
        -16.9058         = Validation score   (-mean_absolute_error)
        0.53s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 99.09s of the
99.06s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -17.4626         = Validation score   (-mean_absolute_error)
        4.1s     = Training   runtime
        0.19s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 93.71s of the 93.69s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -17.171  = Validation score   (-mean_absolute_error)
        2.45s    = Training   runtime
        0.07s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 90.04s of the
90.02s of remaining time.
        -16.909  = Validation score   (-mean_absolute_error)
        9.77s    = Training   runtime
        0.89s    = Validation runtime
Fitting model: CatBoost_BAG_L2 … Training model for up to 79.05s of the 79.04s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -17.2503         = Validation score   (-mean_absolute_error)
        7.13s    = Training   runtime
        0.04s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L2 … Training model for up to 70.72s of the
70.71s of remaining time.
        -16.7678         = Validation score   (-mean_absolute_error)
        1.7s     = Training   runtime
        1.0s     = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L2 … Training model for up to 67.65s of the
```

```
67.64s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -16.9428         = Validation score   (-mean_absolute_error)
        31.92s   = Training   runtime
        0.63s    = Validation runtime
Fitting model: XGBoost_BAG_L2 … Training model for up to 34.45s of the 34.44s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -17.0161         = Validation score   (-mean_absolute_error)
        3.34s    = Training   runtime
        0.1s     = Validation runtime
Fitting model: NeuralNetTorch_BAG_L2 … Training model for up to 29.85s of the
29.84s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -17.214  = Validation score   (-mean_absolute_error)
        25.68s   = Training   runtime
        0.56s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L2 … Training model for up to 2.93s of the
2.92s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -18.602  = Validation score   (-mean_absolute_error)
        3.2s     = Training   runtime
        0.08s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 299.74s of the
-1.61s of remaining time.
        -16.5349         = Validation score   (-mean_absolute_error)
        0.58s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 302.22s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_89_C/")
Evaluation: mean_absolute_error on test data: -33.45657412906985
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -33.45657412906985,
    "root_mean_squared_error": -69.1526037399097,
    "mean_squared_error": -4782.082604008972,
    "r2": 0.749274551565037,
    "pearsonr": 0.8849729932242641,
    "median_absolute_error": -2.6433258056640625
```

```
}
```

```
Evaluation on test data:
-33.45657412906985
```

3 Submit

[12]:
```python
import pandas as pd
import matplotlib.pyplot as plt

train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])

test_data = TabularDataset('X_test_raw.csv')
test_data["ds"] = pd.to_datetime(test_data["ds"])
#test_data
```

```
Loaded data from: X_train_raw.csv | Columns = 56 / 56 | Rows = 93023 -> 93023
Loaded data from: X_test_raw.csv | Columns = 55 / 55 | Rows = 4608 -> 4608
```

[13]:
```python
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
test_data_merged = pd.merge(test_data, test_ids, how="inner", right_on=["time",␣
↪"location"], left_on=["ds", "location"])

#test_data_merged
```

```
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160
```

[ ]:
```python
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in test_data.groupby('location'):
    i = location_map[loc]
    subset = test_data_merged[test_data_merged["location"] == loc].
↪reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)

    # get past predictions
```

```
    past_pred = predictors[i].
↪predict(train_data_with_dates[train_data_with_dates["location"] == loc])
    train_data_with_dates.loc[train_data_with_dates["location"] == loc,␣
↪"prediction"] = past_pred
```

```
[ ]: # plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
↪y='y', ax=ax, label="train data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # plot past predictions
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
↪y='prediction', ax=ax, label="past predictions")

    # title
    ax.set_title(f"Predictions for location {loc}")
```

```
[ ]: # concatenate predictions
submissions_df = pd.concat(predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

```
[ ]: # Save the submission DataFrame to submissions folder, create new name based on␣
↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),␣
↪index=False)
print("jall1a")
```

```
[ ]: # save this running notebook
from IPython.display import display, Javascript
import time

# hei123

display(Javascript("IPython.notebook.save_checkpoint();"))

time.sleep(3)
```

[ ]:
```
# save this notebook to submissions folder
import subprocess
import os
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
 ↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
 ↪ipynb"])
```

[ ]:
```
# feature importance
location="A"
split_time = pd.Timestamp("2022-10-28 22:00:00")
estimated = train_data_with_dates[train_data_with_dates["ds"] >= split_time]
estimated = estimated[estimated["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=estimated,␣
 ↪time_limit=60*10)
```

[ ]:
```
# feature importance
observed = train_data_with_dates[train_data_with_dates["ds"] < split_time]
observed = observed[observed["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=observed,␣
 ↪time_limit=60*10)
```

[ ]:
```
display(Javascript("IPython.notebook.save_checkpoint();"))
time.sleep(3)

subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
 ↪join('notebook_pdfs', f"{new_filename}_with_feature_importance.pdf"),␣
 ↪"autogluon_each_location.ipynb"])
```

[ ]:
```
# import subprocess

# def execute_git_command(directory, command):
#     """Execute a Git command in the specified directory."""
#     try:
#         result = subprocess.check_output(['git', '-C', directory] + command,␣
 ↪stderr=subprocess.STDOUT)
#         return result.decode('utf-8').strip(), True
#     except subprocess.CalledProcessError as e:
#         print(f"Git command failed with message: {e.output.decode('utf-8').
 ↪strip()}")
#         return e.output.decode('utf-8').strip(), False

# git_repo_path = "."

# execute_git_command(git_repo_path, ['config', 'user.email',␣
 ↪'henrikskog01@gmail.com'])
# execute_git_command(git_repo_path, ['config', 'user.name', hello if hello is␣
 ↪not None else 'Henrik eller Jørgen'])
```

```
# branch_name = new_filename

# # add datetime to branch name
# branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"

# commit_msg = "run result"

# execute_git_command(git_repo_path, ['checkout', '-b',branch_name])

# # Navigate to your repo and commit changes
# execute_git_command(git_repo_path, ['add', '.'])
# execute_git_command(git_repo_path, ['commit', '-m',commit_msg])

# # Push to remote
# output, success = execute_git_command(git_repo_path, ['push',␣
↪'origin',branch_name])

# # If the push fails, try setting an upstream branch and push again
# if not success and 'upstream' in output:
#     print("Attempting to set upstream and push again...")
#     execute_git_command(git_repo_path, ['push', '--set-upstream',␣
↪'origin',branch_name])
#     execute_git_command(git_repo_path, ['push', 'origin', 'henrik_branch'])

# execute_git_command(git_repo_path, ['checkout', 'main'])
```